Title: Big team science as a response to urgent societal developments

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Abstract: When responding to urgent societal developments – e.g., the rise of terrorism networks, global pandemics, and new disruptive technologies like AI – researchers often form collaborations that are ultra-large in size. The present work evaluates the impact of these big team science initiatives via an examination of a near-population of 2,150,491 scholarly articles published on terrorism, COVID-19, and ChatGPT. Results indicate that big team science is (a) an increasingly common response to urgent societal developments, that (b) is associated with increased impact on science, policy, and news, with (c) currently little-to-no concomitant delay in published insights. As we prepare responses to both existing and future urgent challenges, there is a pressing need to address existing barriers to mass collaboration in order to maximize the societal impact of science.

Main Text: The first quarter of the 21st century has presented society with numerous developments that have demanded quick and urgent action, including: (a) some of the deadliest terrorist attacks in modern history, (b) a global pandemic, and (c) the ongoing rise of transformative AI technologies. Such developments are often met with a vigorous response from various sectors of society – including scientists and the stakeholders they strive to impact. The present work focuses on these scientific responses, evaluating the role of a recent trend: big team science (*1*).

The present work focuses on research published by relatively small (1 – 4 co-authors) vs. big research teams (up to 100+ co-authors) during three significant societal events: one historical (the September 11, 2001 terrorism attacks), one recent (the COVID-19 pandemic), and one ongoing (the public release of the generative AI tool, ChatGPT). We examine a near-population of research on these topics via OpenAlex: an openly available catalogue of scientific articles (*2*). To index impact, we evaluate how often these articles are discussed in other scholarly publications, news outlets, and policy documents. For the latter two outcomes, we draw upon data from Altmetric: a proprietary service that tracks and measures online engagement with scholarly works. Last, we evaluate the speed at which researchers responded to these societal events by examining articles' publication dates.

Results indicate that big team science is (a) an increasingly common response to urgent societal developments, that (b) is associated with increased impact on science, policy, and news, with (c) currently little-to-no concomitant delay in published insights. These results are described in fuller detail below.

Researchers are increasingly responding to urgent societal developments with big team science

Consistent with broader trends in science (*3*), big team science is an increasingly common response to urgent societal developments. As an example, we compare researchers' response to the COVID-19 pandemic to an event that occurred nearly two decades prior: the September 11 terrorism attacks.

The September 11 attacks caused an estimated $10 billion in infrastructure damage, led to multi-decade military campaigns costing an estimated $4 trillion, and produced a multi-national flurry of policies designed to combat terrorism (*4*). The attacks also generated a sizeable response from scientists. Researchers have used the term 'terrorism' in 322,878 articles – 89.81% of which were published after the September 11 attacks. This research has been overwhelmingly published by relatively small teams. Approximately 93.66% of articles have fewer than 5 co-authors and 5.42% have between 5 and 9 co-authors. Less than 1% of articles on terrorism have 10 or more co-authors – and these historical big team efforts exhibited diminishing returns in terms of impact (*see SI*).

Nearly two decades later, collaborative infrastructure had evolved substantially when researchers began responding to another urgent development: the COVID-19 pandemic. COVID-19 claimed an estimated 15 million lives over a two year span (*5*), led to sweeping policy changes, and had an estimated $14 trillion economic toll in the U.S. alone (*6*). Compared to the September 11 attacks, researchers' responses were substantially more collaborative. The proportion of published articles with fewer than 5 co-authors decreased by 27.28% (now 66.38%), the proportion of articles with 5 to 9 co-authors increased four-fold (now 23.96%), and the proportion of articles with 10 or more co-authors increased eight-fold (now 8.71%).

Part of the shift towards larger collaborations on COVID-19 was a 37-author Phrase 3 clinical trial describing the mRNA-1273 vaccine (*7*). As we review in the next section, the unusually high impact of this big team effort is not an exception – but rather part of a generalizable trend in research on COVID-19.

When responding to the COVID-19 pandemic, bigger teams had more impact on science, the news, and policy – with little-to-no speed tradeoff

To evaluate the impact of big teams during the COVID-19 pandemic, we first consider the relatively small team efforts typically seen in science (Fig. 1). In research on COVID-19, articles published by teams of 1 - 4 co-authors (N = 1,240,191) were mentioned, on average, in 5.51 scholarly works (SD = 41.35), 1.53 news outlets (SD = 15.55), and 0.10 policy documents (SD = 0.80). Comparatively, articles with 10 – 19 co-authors (N = 143,539) were mentioned 3.28 times more in scholarly works (M = 18.07, SD = 125.11), 2.68 times more in news outlets (M = 4.11, SD = 37.21), and 1.80 times more in policy documents (M = 0.18, SD = 1.34). As an even more extreme comparison, consider COVID-19 articles with 100 or more co-authors (N = 1,635). Compared to small team efforts, these ultra-large collaborations were mentioned 17.06 times more in scholarly works (M = 93.98, SD = 381.37), 21.94 times more in news outlets (M = 33.64, SD = 139.23), and 9.63 times more in policy documents (M = 0.99, SD = 4.97).

Of note, big teams did not usually encounter significant time delays (Fig. 1). In fact, they often published scientific insights *quicker* than their small team counterparts. On average, small teams of 1 - 4 co-authors published their insights 780.15 days after the World Health Organization declared a pandemic on March 11, 2020. Larger teams of 10 – 19 co-authors published at a similar speed (M = 783.65 days) – and the quickest insights tended to come from teams of 40 – 49 co-authors (M = 716.55 days). Some exceptions exist, of course. For example, compared to small teams of 1 – 4 co-authors, the largest teams of 100+ co-authors were indeed slower (M = 834.75 days). However, one might argue that the cost of their 54-day delay is offset by the benefits of their 17-fold increase in scientific citations, 22-fold increase in news mentions, and 10-fold increase in references in policy documents.

Looking forward: How are scientists collaboratively tackling the emergence of transformative AI technologies?

Almost two years after developing vaccines to combat the COVID-19 virus, scientists encountered yet another urgent global development: the public release of the AI chatbot, ChatGPT. Although certainly not the only technology on the market, ChatGPT is often considered one of the most influential – receiving credit for accelerating an AI boom whose economic, social, and environmental impacts are rapidly evolving but still unknown (*8*). Furthermore, the phrase “ChatGPT” is virtually nonexistent in the scientific literature before the product’s release (November, 2022). Like research on terrorism and COVID-19, this provides a unique methodological opportunity to evaluate scientists’ response time.

The first few years of published research on ChatGPT (N = 35,940) provide preliminary insights into how researchers are responding to this new urgent development. Similar to the COVID-19 pandemic, researchers’ responses signal a shift towards big teams – with 4.45% of published articles having 10 or more co-authors. There are too few papers to reliably evaluate the impact of their largest collaborative responses; articles with 40-49 authors (N = 19), 60-69 authors (N = 6), and 80-89 authors (N = 1) are still rare (*see SI*). Nonetheless, the pattern observed in collaborations up to those sizes suggest that history may very well repeat itself: big teams will have an outsized impact on the development and understanding of emerging AI technology.

Once again, we first consider the norm: papers published by smaller teams of 1 – 4 co-authors (*N* = 26,324; 73.24%). In research on ChatGPT, these relatively small teams have received an average 4.66 mentions in other scholarly work (*SD* = 27.05) 1.48 mentions in the news (*SD* = 17.96) and 0.03 mentions in policy documents (*SD* = 0.43). Comparatively, the 1,392 articles with 10 - 19 co-authors have received 2.70 times more mentions in scholarly works (*M* = 12.58, *SD* = 69.79), 2.21 times more mentions in news (*M* = 3.27, *SD* = 28.53), and a similar number of mentions in policy documents (*M* = 0.03, *SD* = 0.30). The 106 articles with 20 – 29 co-authors have fared even better, receiving 7.99 times more mentions in scholarly works (*M* = 37.27, *SD* = 169.64), 1.32 times more mentions in news (*M* = 1.96, *SD* = 5.51), and 3.99 times more mentions in policy documents (*M* = 0.13, *SD* = 0.60). Once again, these larger collaborations are achieving increased impact with minimal speed tradeoffs. On average, small teams of 1 – 4 co-authors published their insights 5.72 days quicker than teams of 5 – 9, 19.20 days quicker than teams of 10 – 19, and 19.13 days slower than teams of 30 – 39 co-authors.

Outstanding issues: Facilitating, understanding, and balancing big team efforts in science

The tendency for bigger teams in science to produce higher impact work during urgent societal developments is at odds with another finding: such collaborations are relatively unusual. Fortunately, previous investigations have provided multiple clues as to why this gap exists. For example, researchers have noted that collaborative efforts are undervalued in academic evaluations, difficult to fund, and challenging to reconcile with existing publication norms (*9*). Furthermore, researchers are not usually trained on how to most effectively contribute to team-based science (*10*) – e.g., how to handle the disagreements that are sometimes inevitable in large groups (*9*). Addressing these barriers requires changing the way that scientists are trained, evaluated, funded, and promoted. This change is itself an urgent priority – one we should work to address before we're faced with our next major societal development.

The tendency for bigger teams in science to produce higher impact work also raises questions about what mechanisms drive their success. One possibility, of course, is that big teams exhibit collective intelligence – e.g., combine their expertise to select better ideas and/or conduct higher-quality investigations. Consistent with this idea, past research has shown that crowdsourcing the perspectives of scientists can be leveraged to predict the replicability of published findings (*11*) and the number of citations that a manuscript will receive (*12*). However, it is also possible that the impact of big teams is exaggerated by social biases, such as increases in self-promotion and/or bandwagon effects. Future research can begin to disentangle these effects, for instance, via blind evaluations of research conducted by large vs. small teams.

Last, efforts to facilitate and understand big team science should also seek to identify their ideal balance. Although the efficacy of the mRNA-1273 vaccine was described by a large team, many key discoveries related to mRNA were made by small teams – including the Nobel prize winning work of Karikó, Buckstein, Ni, and Weissman (*13*). The best approach to addressing urgent global developments likely isn't to focus exclusively on big team or small team efforts – but rather to find a better balance between their unique benefits.

Concluding remarks

In summary, the present work highlights the growing role of big team science as a response to urgent societal developments. The analysis of research following the September 11 attacks, COVID-19 pandemic, and release of transformative AI technologies like ChatGPT reveals a trend: during urgent societal developments, researchers are increasingly coming together en masse to produce timely and high-impact insights. Indeed, an influential paper describing GPT-4 was co-authored by a team of over 200 authors (*14*) – as was a paper describing an influential competitor, DeepSeek (*15*). Despite the impact of ultra-large collaborations, they remain relatively uncommon due to barriers related to funding, training, evaluation, and publication norms. As we prepare for future urgent challenges, we must adapt our existing frameworks to not just accommodate but also encourage scientists to leverage the power of mass collaboration to maximize societal impact.

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Supplementary Materials

Materials and Methods

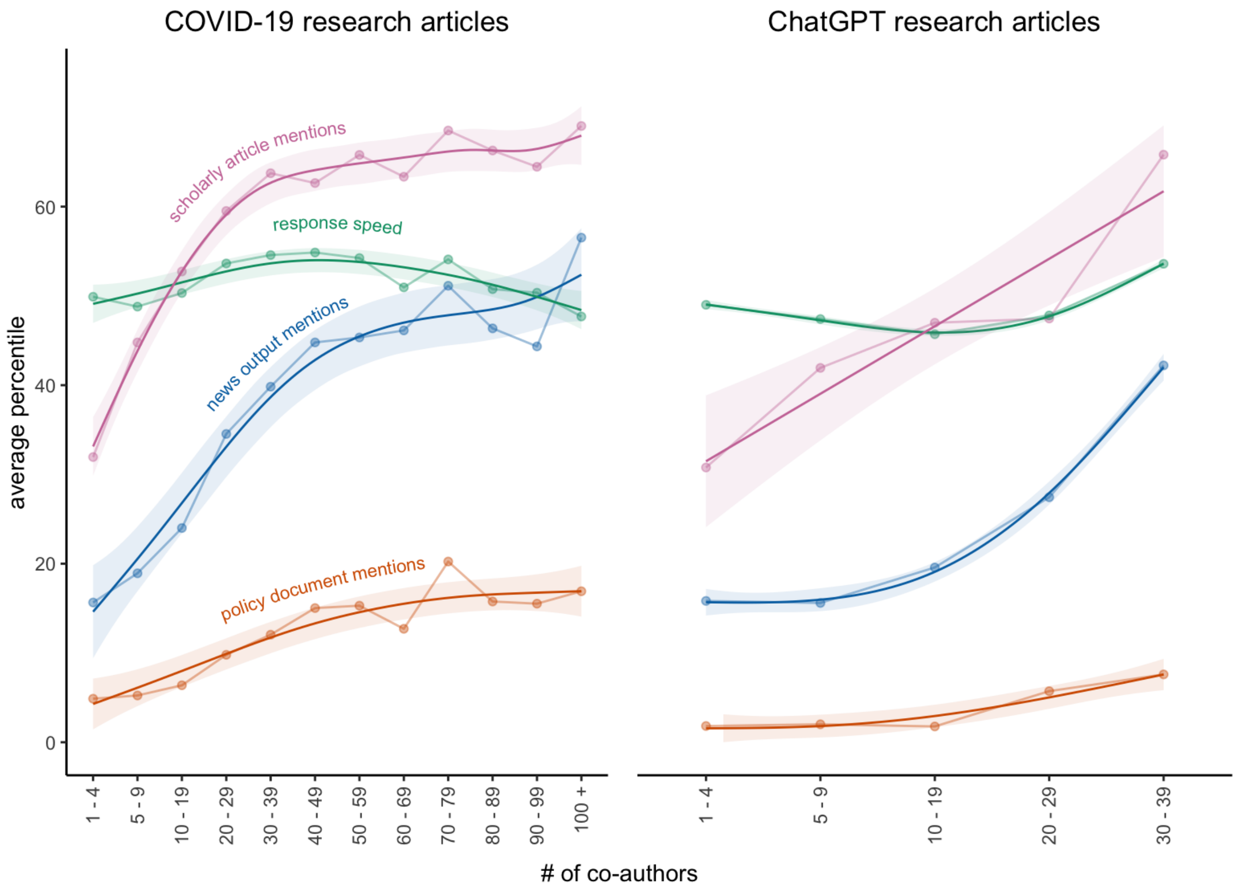
Supplementary Text

Figs. S1 to S4

Tables. S1 to S4

Fig. 1. Impact and response speed of research conducted on COVID-19 and ChatGPT. In researchers' responses to COVID-19 and ChatGPT, articles published by bigger teams have received higher average mentions in scholarly articles (pink), news outputs (blue), and policy

documents (orange). Bigger teams have also exhibited little-to-no difference in response speed (green), showing small improvements in response time in some cases and small decreases in response time in other cases. In the graph below, dots indicate average percentiles. Solid dark lines represent relationships estimated via generalized additive models, and colored bands represent 95% confidence intervals. For select outcomes, dotted lines highlight raw differences between the smallest and largest collaborations studied.



Supplemental Materials: The work focuses on a near-population of articles linked to keywords "terrorism", "COVID-19", and "ChatGPT". These records were accessed in September 2024 (October 2024 for COVID-19 records) via OpenAlex: an open-source bibliographic catalogue of scientific papers.

Records were removed if they (a) had duplicative DOI's, (b) did not contain any authorship meta-data, or (c) were published before an event signaled the societal development. For the latter, terrorism papers had to be published after the date of the attacks (September 11, 2001); COVID-19 records had to be published after the first cases emerged in November 2019; ChatGPT records had to published after the public release of the tool (November 30, 2022). This left us with N = 289,986 terrorism papers, N = 1,824,565 COVID-19 paper, and N = 35,940 ChatGPT papers.

Team size was extracted using OpenAlex authorship meta-data. Because there is no precise definition of "big team science" (Baumgartner et al., 2023), the present work describes multiple granular operationalizations: publications with (a) 10 - 19 authors, (b) 20 - 29 authors, (c) 30 - 39 authors, (d) 40 - 49 authors, (e) 50 - 59 authors, (f) 60 - 69 authors, (g) 70 - 79 authors, (h) 80 - 89 authors, (i) 90 - 99 authors, and (j) 100+ authors. These big team efforts are compared to publications with relatively smaller teams of 1 - 4 and 5 - 9 authors.

For publication speed, we used OpenAlex publication dates to determine how many days had passed since an event signaled an urgent societal development. For terrorism papers, we used September 11, 2001. For COVID-19 papers, we used the date the World Health Organization declared a pandemic (March 11, 2020). For ChatGPT data, we used the date the tool was made publicly available (November 30, 2022).

Descriptive statistics

Tables S1 (terrorism research), S2 (COVID-19 research) and S3 (ChatGPT research) contain descriptive statistics for research speed and mentions in scholarly articles, news outputs, and policy documents.

Examination of big teams in research on terrorism

As mentioned in the main text, research on terrorism has been overwhelmingly published by relatively small teams. However, a sizeable number of papers (N = 2,693) had 10 or more co-authors. An examination of their impact reveals diminishing returns.

First, consider the N = 2,131 articles that had between 10 and 39 articles. Compared to papers co-authored by small teams of 1 – 4 co-authors, these larger collaborations tended to be published later in time. However, these larger collaborations also tended to receive more mentions in scholarly articles, news outputs, and policy documents (Fig. S1). However, impact diminished in the rare instances (N = 208) where researchers published papers with 40 or more co-authors. Based on the limited evidence available, we offer the tentative conclusion described in the main text: ultra-large collaborations on terrorism yielded diminishing returns in terms of impact (Fig. S2).

Examination of ultra-large (and ultra-rare) collaborations in research on ChatGPT

The main text focuses on articles with up to 39 co-authors (Fig. S3) because there isn't enough data to speak confidently about larger collaborations. For example, there are only $N = 19$ articles with 40 – 49 co-authors, $N = 6$ articles with 60 – 69 co-authors, and $N = 1$ article with 80 – 89 co-authors (Table S1).

Based on the limited evidence available for these ultra-large collaborations, we offer this tentative conclusion: increases in team size were reliably associated with increases in mentions in scholarly articles; for mentions in policy documents and the general population, however, the biggest teams exhibited diminishing returns (Fig. S4).

Fig. S1. Impact and response time of research conducted on terrorism. Average value (y-axis) of scholarly article mentions, news output mentions, policy document mentions, and response time (panels) for teams of various sizes (x-axis). Dots represent means and error bars represent one standard error.

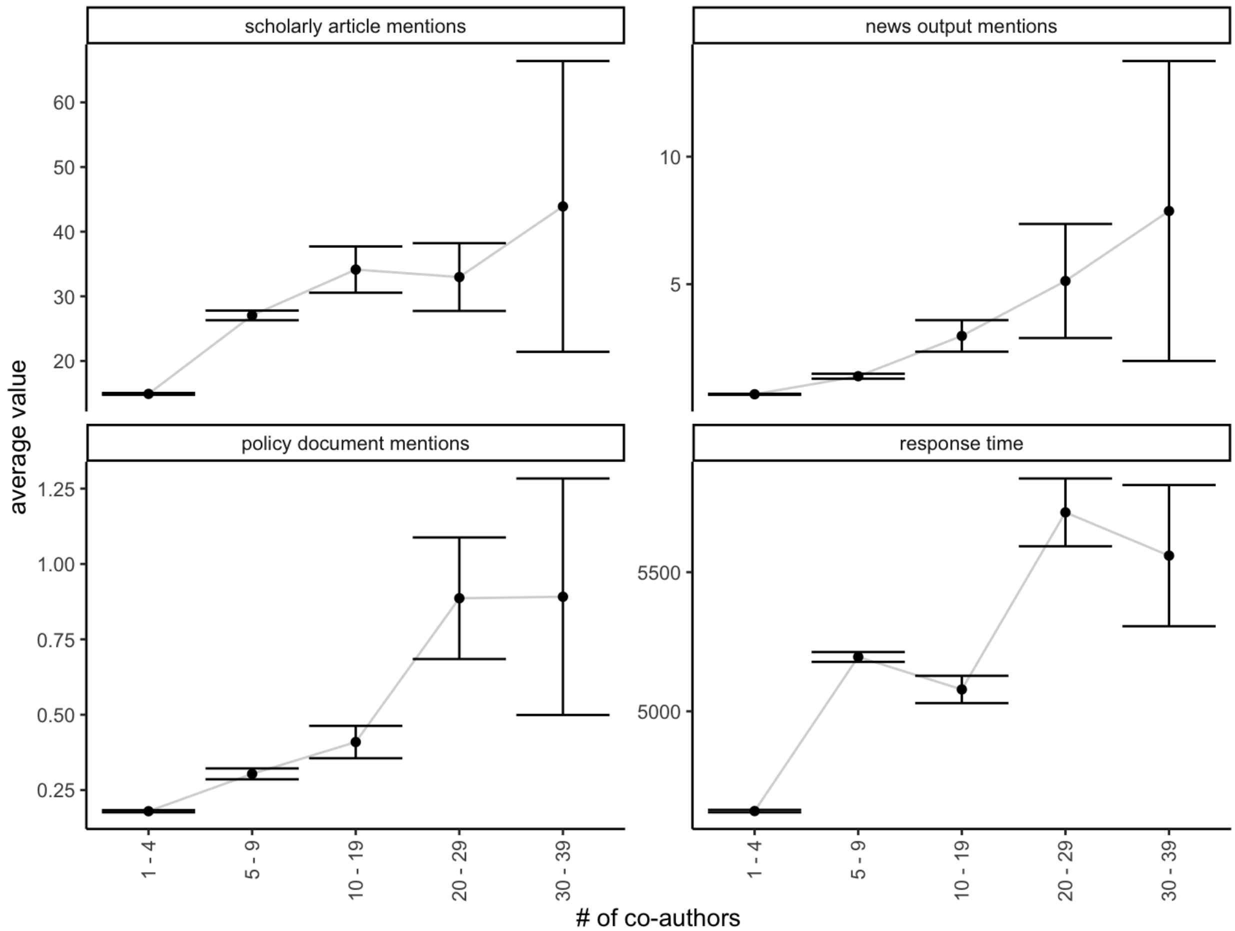


Fig. S2. Impact and response time of research conducted on terrorism (ultra-large collaborations included). Average value (y-axis) of scholarly article mentions, news output mentions, policy document mentions, and response time (panels) for teams of various sizes (x-axis). Dots represent means and error bars represent one standard error.

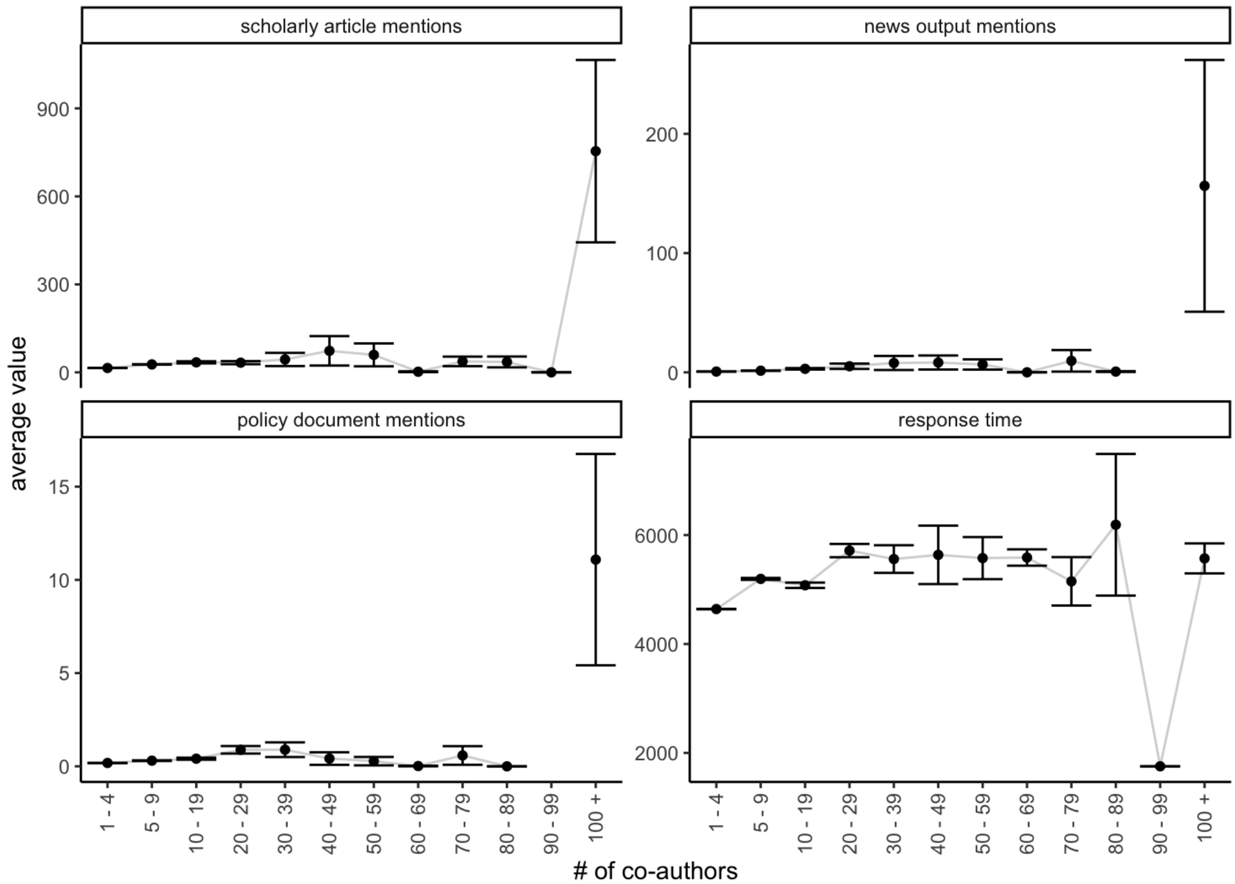


Fig. S3. Impact and response time of research conducted on ChatGPT. Average value (y-axis) of scholarly article mentions, news output mentions, policy document mentions, and response time (panels) for teams of various sizes (x-axis). Dots represent means and error bars represent one standard error.

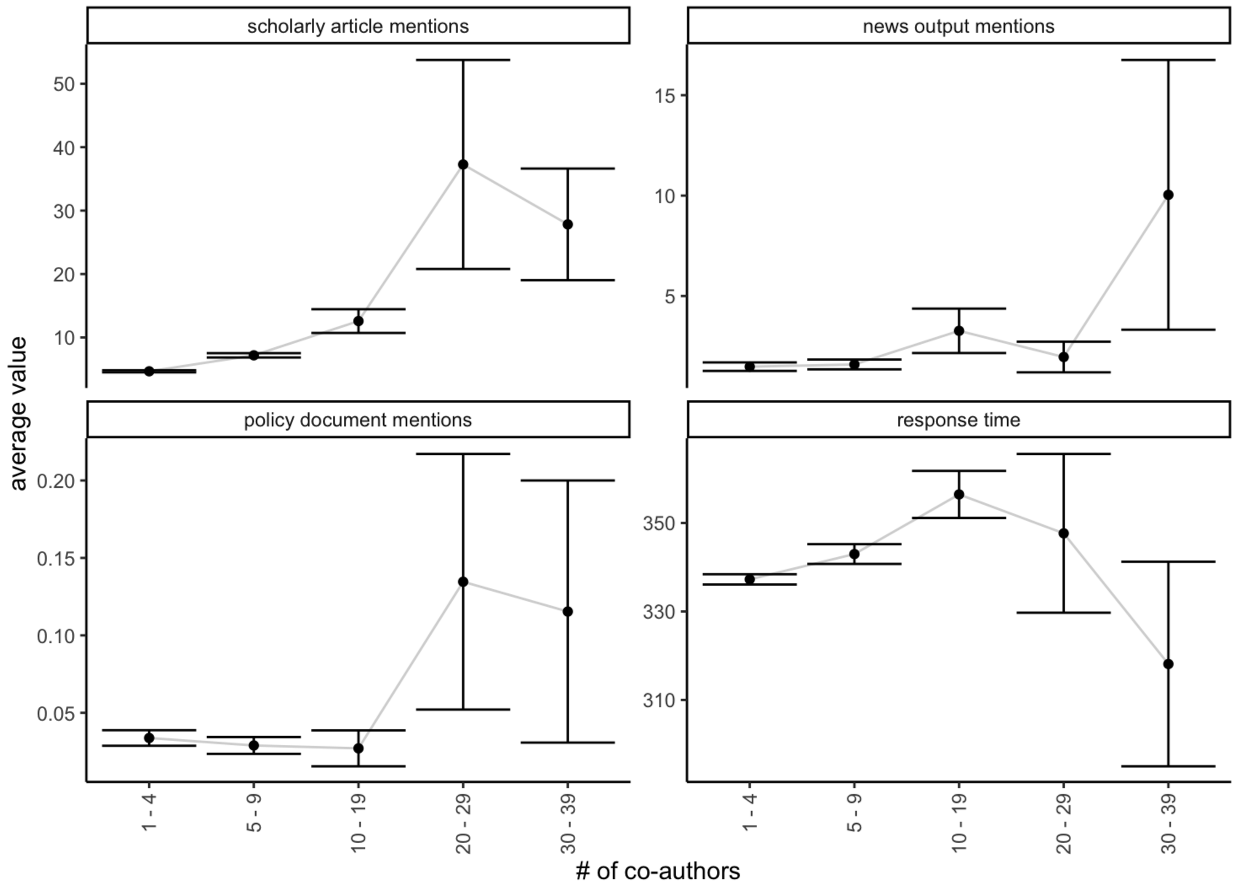


Fig. S4. Impact and response time of research conducted on ChatGPT (ultra-large collaborations included). Average value (y-axis) of scholarly article mentions, news output mentions, policy document mentions, and response time (panels) for teams of various sizes (x-axis). Dots represent means and error bars represent one standard error. Error bars are not plotted in instances with insufficient data (e.g., access to only one observation).

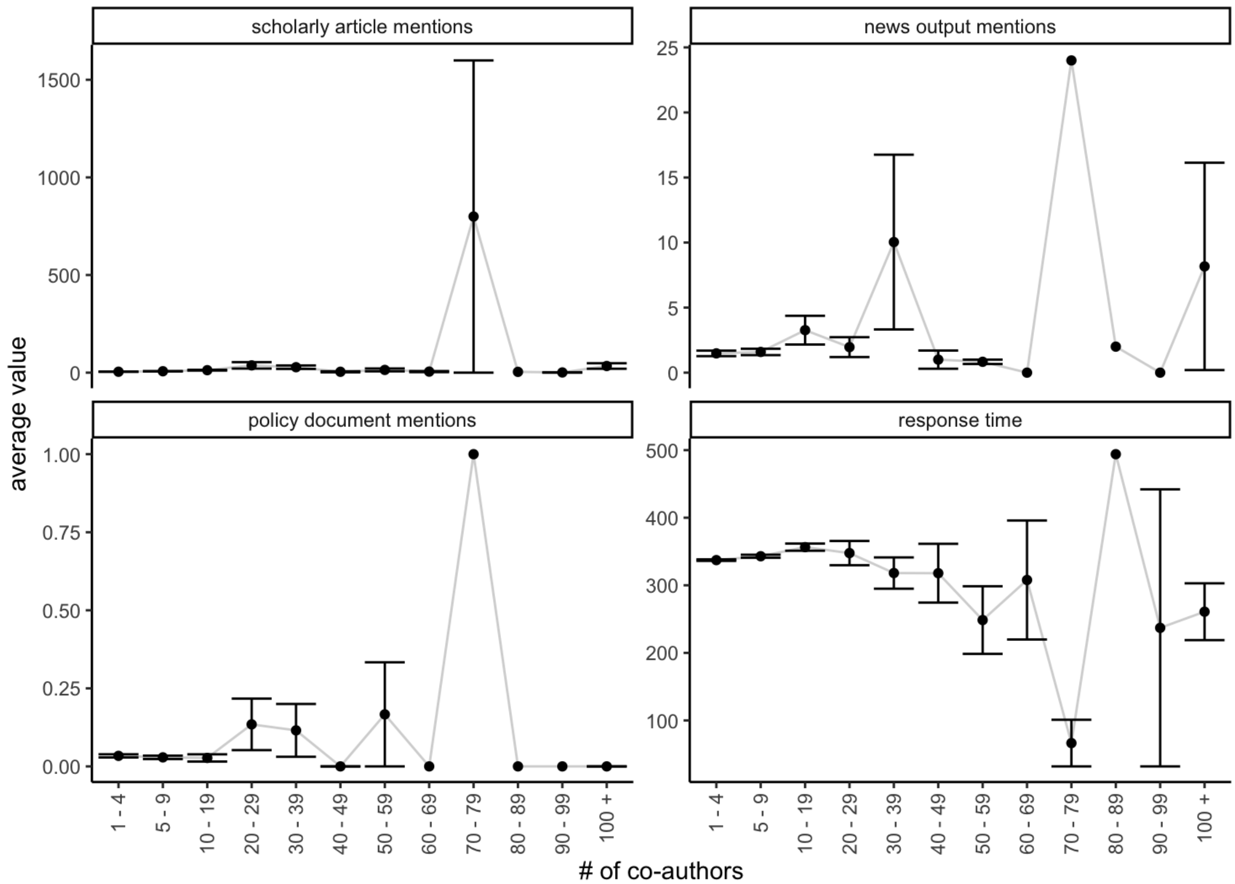


Table S1. Terrorism research speed and mentions in scholarly articles, news outputs, and policy documents. For each team size range, mentions are described in terms of both raw and percentile-transformed values. Also described is the number of articles indexed in OpenAlex (*n*) and the proportion of those articles that received mentions. NA's refer to instances where there was no available data. Also described is response time, in terms of number of days since a notable event signaled an urgent development.

			raw		percentile		
mentions	**team size**	***n***	***M***	***SD***	***M***	***SD***	**proportion of articles mentioned**
scholarly articles	1 - 4	271588	14.91	72.04	41.43	35.41	0.63
scholarly articles	5 - 9	15705	27.05	93.71	55.89	34.81	0.77
scholarly articles	10 - 19	2108	34.14	164.22	53.4	37.02	0.72
scholarly articles	20 - 29	292	32.98	89.51	49.24	38.81	0.67
scholarly articles	30 - 39	85	43.91	207.33	45.91	38.39	0.65
scholarly articles	40 - 49	26	73.38	255.82	33.57	39.59	0.46
scholarly articles	50 - 59	31	59.61	217.71	35.51	40.17	0.48
scholarly articles	60 - 69	73	2.16	12.82	10.94	23.28	0.21
scholarly articles	70 - 79	21	37.38	74.87	29.3	41.71	0.38
scholarly articles	80 - 89	4	35.5	36.99	75.81	23.34	1
scholarly articles	90 - 99	2	0	0	0	0	0
scholarly articles	100 +	51	754.18	2220.76	42.38	45.78	0.49
news outputs	1 - 4	271588	0.68	6.74	13.58	32.32	0.15
news outputs	5 - 9	15705	1.39	8.51	16.04	34.83	0.18
news outputs	10 - 19	2108	2.97	21.53	19.85	37.96	0.22
news outputs	20 - 29	292	5.12	29.66	27.43	42.6	0.3
news outputs	30 - 39	85	7.87	39.89	26.88	43.36	0.28
news outputs	40 - 49	26	8.25	20.39	30.73	45.62	0.33

			raw		percentile		
mentions	**team size**	***n***	***M***	***SD***	***M***	***SD***	**proportion of articles mentioned**
news outputs	50 - 59	31	6.61	18.31	26.48	44.05	0.28
news outputs	60 - 69	73	0.05	0.28	2.85	15.75	0.03
news outputs	70 - 79	21	9.67	31.31	31.03	45.96	0.33
news outputs	80 - 89	4	0.67	0.58	56.44	48.88	0.67
news outputs	90 - 99	2	NA	NA	NA	NA	NA
news outputs	100 +	51	156.39	506.2	64.59	48.24	0.65
policy documents	1 - 4	271588	0.18	1.15	8.62	26.96	0.09
policy documents	5 - 9	15705	0.3	1.59	12.36	31.7	0.13
policy documents	10 - 19	2108	0.41	1.87	13.53	33.13	0.14
policy documents	20 - 29	292	0.89	2.67	19.07	38.42	0.2
policy documents	30 - 39	85	0.89	2.66	16.67	36.78	0.17
policy documents	40 - 49	26	0.42	1.16	15.78	36.9	0.17
policy documents	50 - 59	31	0.28	0.96	10.52	30.65	0.11
policy documents	60 - 69	73	0.02	0.13	1.46	11.48	0.02
policy documents	70 - 79	21	0.58	1.73	15.82	37.01	0.17
policy documents	80 - 89	4	0	0	0	0	0
policy documents	90 - 99	2	NA	NA	NA	NA	NA
policy documents	100 +	51	11.09	27.18	55.16	49.53	0.57
response time	1 - 4	271588	4641.4	2270.6	50.35	28.8	
response time	5 - 9	15705	5195.4	2209.63	43.17	28.78	
response time	10 - 19	2108	5078.55	2254.54	44.6	29.24	

mentions	team size	*n*	raw *M*	raw *SD*	percentile *M*	percentile *SD*	proportion of articles mentioned
response time	20 - 29	292	5715.01	2080.42	36.2	27.46	
response time	30 - 39	85	5559.58	2340.22	37.53	29.98	
response time	40 - 49	26	5636.62	2735.63	35.94	35.38	
response time	50 - 59	31	5577.13	2151.62	37.61	27.6	
response time	60 - 69	73	5587.62	1279.2	39.66	15.45	
response time	70 - 79	21	5150.48	2038.11	44.18	28.09	
response time	80 - 89	4	6189	2600.98	28.68	34.9	
response time	90 - 99	2	1754	0	85.91	0	
response time	100 +	51	5571.39	1965.24	38.61	27.1	

Table S2. COVID-19 research speed and mentions in scholarly articles, news outputs, and policy documents. For each team size range, mentions are described in terms of both raw and percentile-transformed values. Also described is the number of articles indexed in OpenAlex (*n*) and the proportion of those articles that received mentions. Also described is response time, in terms of number of days since a notable event signaled an urgent development.

			raw		percentile		
mentions	**team size**	***n***	***M***	***SD***	***M***	***SD***	**proportion of articles mentioned**
scholarly articles	1 - 4	1208365	5.33	34.9	31.95	35.99	0.47
scholarly articles	5 - 9	438876	10.31	51.95	44.79	38.25	0.61
scholarly articles	10 - 19	141051	17.12	90.79	52.73	38.24	0.69
scholarly articles	20 - 29	22333	33.7	200.75	59.51	37.9	0.74
scholarly articles	30 - 39	6358	49.26	218.86	63.74	37.37	0.77
scholarly articles	40 - 49	2788	62.72	264.83	62.64	38.99	0.75
scholarly articles	50 - 59	1286	64.7	227.43	65.79	36.92	0.79
scholarly articles	60 - 69	817	55.9	257.43	63.35	37.93	0.76
scholarly articles	70 - 79	422	81.45	222.02	68.53	37.69	0.79
scholarly articles	80 - 89	378	70.22	229.25	66.29	37.45	0.79
scholarly articles	90 - 99	260	77.53	215.22	64.46	38.88	0.76
scholarly articles	100 +	1631	94.2	381.81	69.03	37.15	0.8
news outputs	1 - 4	1208365	1.52	15.33	15.66	33.37	0.18
news outputs	5 - 9	438876	2.32	21.76	18.93	35.92	0.22
news outputs	10 - 19	141051	4.07	36.95	24	39.19	0.28
news outputs	20 - 29	22333	8.53	53.41	34.54	43.65	0.39
news outputs	30 - 39	6358	15.75	77.22	39.83	45.12	0.44
news outputs	40 - 49	2788	18.93	95.06	44.79	45.68	0.49
news outputs	50 - 59	1286	20.82	79.18	45.34	45.82	0.5

			raw		percentile		
mentions	**team size**	***n***	***M***	***SD***	***M***	***SD***	**proportion of articles mentioned**
news outputs	60 - 69	817	16.94	65.56	46.13	45.81	0.51
news outputs	70 - 79	422	23.19	71.57	51.14	45.8	0.56
news outputs	80 - 89	378	22.48	85.8	46.36	46.31	0.5
news outputs	90 - 99	260	30.78	107.59	44.34	46.09	0.49
news outputs	100 +	1631	33.71	139.38	56.53	44.96	0.62
policy documents	1 - 4	1208365	0.1	0.76	4.88	21.06	0.05
policy documents	5 - 9	438876	0.12	0.91	5.24	21.81	0.05
policy documents	10 - 19	141051	0.18	1.29	6.38	23.95	0.07
policy documents	20 - 29	22333	0.36	2.27	9.8	29.16	0.1
policy documents	30 - 39	6358	0.62	3.8	12.05	31.99	0.12
policy documents	40 - 49	2788	0.71	3.49	15.03	35.13	0.15
policy documents	50 - 59	1286	0.89	3.85	15.3	35.46	0.16
policy documents	60 - 69	817	0.69	3.39	12.71	32.73	0.13
policy documents	70 - 79	422	1.2	5.62	20.24	39.55	0.21
policy documents	80 - 89	378	1.19	6	15.77	35.83	0.16
policy documents	90 - 99	260	1.19	5.84	15.53	35.62	0.16
policy documents	100 +	1631	0.99	4.97	16.92	36.88	0.17
response time	1 - 4	1208365	802.48	408.51	49.91	28.54	
response time	5 - 9	438876	819.23	417.84	48.8	29.08	
response time	10 - 19	141051	798.59	427.24	50.32	29.68	
response time	20 - 29	22333	750.92	428.76	53.63	29.75	

			raw		percentile		
mentions	**team size**	***n***	***M***	***SD***	***M***	***SD***	**proportion of articles mentioned**
response time	30 - 39	6358	738.58	431.34	54.58	29.93	
response time	40 - 49	2788	733.63	413.54	54.86	28.74	
response time	50 - 59	1286	742.67	426.01	54.24	29.57	
response time	60 - 69	817	788.56	429.14	50.95	29.93	
response time	70 - 79	422	742.71	413.95	54.09	28.89	
response time	80 - 89	378	792.41	429.02	50.76	30.02	
response time	90 - 99	260	795.78	401.22	50.36	28.32	
response time	100 +	1631	836.97	408	47.7	28.56	

Table S3. ChatGPT research speed and mentions in scholarly articles, news outputs, and policy documents. For each team size range, mentions are described in terms of both raw and percentile-transformed values. Also described is the number of articles indexed in OpenAlex (*n*) and the proportion of those articles that received mentions. Also described is response time, in terms of number of days since a notable event signaled an urgent development. NA's refer to instances where the value could not be computed (e.g., because of zero variance).

			raw		percentile		
mentions	**team size**	***n***	***M***	***SD***	***M***	***SD***	**proportion of articles mentioned**
scholarly articles	1 - 4	26324	4.66	27.05	30.78	37.35	0.42
scholarly articles	5 - 9	8017	7.18	30.48	41.94	39.54	0.55
scholarly articles	10 - 19	1392	12.58	69.79	46.99	39.83	0.61
scholarly articles	20 - 29	106	37.27	169.64	47.47	42.16	0.58
scholarly articles	30 - 39	41	27.83	56.35	65.82	35.81	0.8
scholarly articles	40 - 49	19	4.42	10.99	30.48	41.48	0.37
scholarly articles	50 - 59	11	13.91	24.15	42.94	49.38	0.45
scholarly articles	60 - 69	6	5.33	6.5	55.1	43.52	0.67
scholarly articles	70 - 79	2	799.5	1130.66	50	70.71	0.5
scholarly articles	80 - 89	1	4	NA	79.06	NA	1
scholarly articles	90 - 99	2	1	1.41	33.89	47.93	0.5
scholarly articles	100 +	19	34	61.09	48.26	44.59	0.58
news outputs	1 - 4	26324	1.48	17.96	15.83	34	0.18
news outputs	5 - 9	8017	1.59	13.04	15.6	33.89	0.18
news outputs	10 - 19	1392	3.27	28.53	19.58	37.09	0.22
news outputs	20 - 29	106	1.96	5.51	27.45	41.76	0.31
news outputs	30 - 39	41	10.04	34.24	42.21	46.72	0.46
news outputs	40 - 49	19	1	2.21	26.85	43.36	0.3

			raw		percentile		
mentions	**team size**	***n***	***M***	***SD***	***M***	***SD***	**proportion of articles mentioned**
news outputs	50 - 59	11	0.83	0.41	68.1	33.36	0.83
news outputs	60 - 69	6	0	NA	0	NA	0
news outputs	70 - 79	2	24	NA	98.68	NA	1
news outputs	80 - 89	1	2	NA	90.5	NA	1
news outputs	90 - 99	2	0	NA	0	NA	0
news outputs	100 +	19	8.17	19.52	30.18	47.08	0.33
policy documents	1 - 4	26324	0.03	0.43	1.82	13.27	0.02
policy documents	5 - 9	8017	0.03	0.29	2.01	13.92	0.02
policy documents	10 - 19	1392	0.03	0.3	1.77	13.08	0.02
policy documents	20 - 29	106	0.13	0.6	5.72	23.36	0.06
policy documents	30 - 39	41	0.12	0.43	7.6	26.85	0.08
policy documents	40 - 49	19	0	0	0	0	0
policy documents	50 - 59	11	0.17	0.41	16.34	40.03	0.17
policy documents	60 - 69	6	0	NA	0	NA	0
policy documents	70 - 79	2	1	NA	98.06	NA	1
policy documents	80 - 89	1	0	NA	0	NA	0
policy documents	90 - 99	2	0	NA	0	NA	0
policy documents	100 +	19	0	0	0	0	0
response time	1 - 4	26324	337.26	188.69	49	26.99	
response time	5 - 9	8017	342.98	199.79	47.41	27.98	
response time	10 - 19	1392	356.45	198.3	45.71	28.08	

			raw		percentile		
mentions	**team size**	***n***	***M***	***SD***	***M***	***SD***	**proportion of articles mentioned**
response time	20 - 29	106	347.66	184.73	47.82	26.93	
response time	30 - 39	41	318.12	148.05	53.6	22.33	
response time	40 - 49	19	317.89	189.65	50.83	27.03	
response time	50 - 59	11	248.55	165.99	62.15	21.66	
response time	60 - 69	6	307.83	215.63	48.58	28.24	
response time	70 - 79	2	66.5	48.79	83.54	1.36	
response time	80 - 89	1	494	NA	22.02	NA	
response time	90 - 99	2	237	289.91	58.08	37.36	
response time	100 +	19	260.89	183.16	58.44	24.07	